Constraint Satisfaction Problems

Global Constraints

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1 Motivation

- Global Constraints
- All-different
- Sum and Cardinality
- Circuit

Global constraints

What are global constraints?

- Type of similar constraint relations ...
- ... differing in the number of variables
- Semantically redundant: same constraint can be expressed by a conjunction of simpler constraints
- Similar structure: can be exploited by constraint solvers

Examples:

- sum constraint, knapsack constraint, element constraint, all-different constraint, cardinality constraints

All-different constraint

Definition

Let $v_1, \dots, v_n$ be variables each with a domain D_i ($1 \le i \le n$).

$$\texttt{alldifferent}(v_1, \dots, v_n) := \{(d_1, \dots, d_n) \in D_1 \times \cdots \times D_n : d_i \neq d_j \text{ for } i \neq j\}$$

The all-different constraint is a simple, but widely used global constraint in constraint programming.
It allows for compact modeling of CSP problems.

Example: *n*-Queens Problem

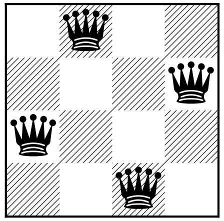

Abbildung: 4-queens problem

No-attack constraints:

$$v_i \neq v_j \text{ for } 1 \leq i < j \leq n$$
$$v_i - v_j \neq i - j \text{ for } 1 \leq i < j \leq n$$
$$v_j - v_i \neq i - j \text{ for } 1 \leq i < j \leq n$$

Problem representation: Variables v_i for each column $1, \dots, n$; v_i can take a "row value" $1, \dots, n$.

$\texttt{alldifferent}(v_1, \dots, v_n)$
$\texttt{alldifferent}(v_1 - 1, \dots, v_n - n)$
$\texttt{alldifferent}(v_1 + 1, \dots, v_n + n)$

Sum constraint

Let $v_1, \dots, v_n, z$ be variables with subsets of $\mathbb{Q}$ as domain. For each v_i, let $c_i \in \mathbb{Q}$ be some fixed scalar, $c = (c_1, \dots, c_n)$.

Definition

The sum constraint is defined as:

$$\texttt{sum}(v_1, \dots, v_n, z; c) := \{(d_1, \dots, d_n, d) \in (\prod_{1 \leq i \leq n} D_i) \times D_z : d = \sum_{1 \leq i \leq n} c_i d_i\}.$$

Global cardinality constraint

$v_1, \dots, v_n$: "assignment variables" with $D_{v_i} \subseteq \{d_1^*, \dots, d_m^*\}$.
$c_1, \dots, c_m$: "count variables" with sets of integers as domains.

Definition

The global cardinality constraint is defined as:

$$\texttt{gcc}(v_1, \dots, v_n, c_1, \dots, c_m) := \{(d_1, \dots, d_n, o_1, \dots, o_m) \in \prod_{1 \leq i \leq n} D_{v_i} \times \prod_{1 \leq j \leq m} D_{c_j} : \text{for each } j, d_j^* \text{ occurs in } (d_1, \dots, d_n) \text{ exactly } o_j \text{ times}\}$$

The global cardinality constraint can be considered a generalization of the all-different constraint.

Circuit constraint

Let $s = (s_1, \dots, s_n)$ be a permutation of $\{1, \dots, n\}$.
Define C_s as the smallest set that contains 1 and with each element i also s_i.
$(s_1, \dots, s_n)$ is called cyclic if $C_s = \{1, \dots, n\}$.

Definition

Let $v_1, \dots, v_n$ be variables with domains $D_i = \{1, \dots, n\}$ $(1 \leq i \leq n)$.

$$\texttt{circuit}(v_1, \dots, v_n) := \{(d_1, \dots, d_n) \in D_1 \times \dots \times D_n : (d_1, \dots, d_n) \text{ is cyclic}\}$$

Given an assignment $a = (d_1, \dots, d_n)$, define

$$A := \{(v_i, v_{d_i}) : d_i \in D_i, 1 \leq i \leq n\}.$$

Then, a satisfies $\texttt{circuit}(v_1, \dots, v_n)$ if and only if (V, A) is a

Example: Traveling Salesperson Problem

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Traveling Salesperson Problem (TSP):

Given a set of n cities and distances c_{ij} between city i and city j, find the shortest route that visits all cities and finishes in the starting city.

TSP is not a constraint satisfaction problem, but a constraint optimization problem …

Constraint optimization problem

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Definition

A constraint optimization problem (COP) is a constraint satisfaction problem together with an objective function f that assigns to each variable assignment a a value $f(a) \in \mathbb{Q}$.

- Minimization COP: Find a solution a that minimizes $f(a)$.
- Maximization COP: Find a solution a that maximizes $f(a)$.
- Optimal solution: Solution to a minimization (maximization) COP.

Decision problem associated to a COP:

Given an instance of a COP, (N, f), and some threshold $t \in \mathbb{Q}$, is there a solution a of P such that $f(a) \geq t$ ($f(a) \leq t$, resp.)?

The decision problem of TSP

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v_i : variable for city i with domain $D_i := \{1, \ldots, n\} \setminus \{i\}$ (read as: value of v_i is the city to be visited next)

c_{ij} : distance between cities i and j (may not be symmetric)

t : bound for the total tour length

Then:

$$\texttt{circuit}(v_1, \ldots, v_n)$$
$$\sum_{1 \leq i \leq n} c_{i v_i} \leq t$$

2 Filtering

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- Arc consistency
- All-different Constraint

Filtering

- Constraint propagation techniques aim at filtering variable domains: remove useless values (that cannot participate in any solution) as early as possible.
- Filtering allows false-positives (values are kept though they are useless),
- …… but not false-negatives (useful values may not be removed).
- A constraint is "good" if it allows significant filtering (pruning of domain values) with low computational efforts.
- Constraint solver may benefit from exploiting the structure of such good constraints.

Filtering by enforcing arc consistency

- In general, enforcing generalized arc consistency on a constraint network requires exponential time w.r.t. the largest arity of some constraint relation in the network.

  Recall: Enforcing generalized arc consistency runs in time

  $$\mathcal{O}(erd^r),$$

  where e is the number of constraints and r is the largest arity of some constraint in the network,
- Though general constraints have often high arity, there exist efficient methods to enforce generalized arc consistency.
- In the following we consider the all-different constraints.

Value graphs

Definition

An undirected graph $G = \langle V, E\rangle$ is bipartite if there exists a partition $S \dot{\cup} T$ of V such that for each $\{x,y\} \in E$, $x \in S$ iff $y \in T$.
A directed graph $G = \langle V, A\rangle$ is bipartite if there exists a partition $S \dot{\cup} T$ of V such that $A \subseteq (S \times T) \cup (T \times S)$.
G is then written in the form $G = \langle S, T, E\rangle$ (resp. $G = \langle S, T, A\rangle$).

Definition

Let V be a set of variables and D be the union of all domains D_v for $v \in V$.
The value graph of V is defined as the following bipartite graph:

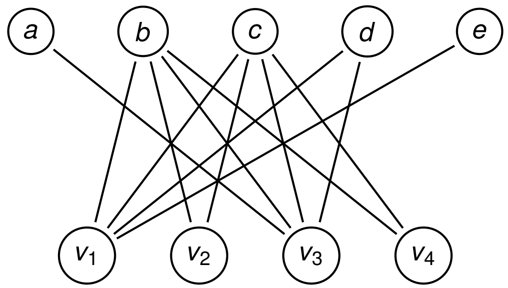
$$G = \langle V, D, E\rangle$$

where $E = \{\{v,d\} : v \in V, d \in D_v\}$.

Example: Value graph

Consider variables $v_1, \ldots, v_4$ with $D_1 = \{b,c,d,e\}$, $D_2 = \{b,c\}$, $D_3 = \{a,b,c,d\}$, $D_4 = \{b,c\}$.

Value graph:



Matchings

Let $G = \langle V, E \rangle$ be an undirected (simple) graph.

Definition

A matching in G is a set $M \subseteq E$ of pairwise disjoint edges.
A matching M covers a set $S \subseteq V$ if $S \subseteq \bigcup M$, i.e., each $v \in S$ is contained in some edge in M.
$v \in V$ is M-free if M does not cover $\{v\}$.

Definition

Let M be a matching in G.
A path $P = v_0, e_1 \ldots, e_k, v_k$ in G is M-alternating if all the edges e_i are alternatingly out of and in M.
An M-alternating path $P = v_0, e_1, \ldots, e_k, v_k$ is called M-augmenting if v_0 and v_k are M-free.

Max-cardinality matching

Let $G = \langle V, E \rangle$ be a graph and M be a matching in G.

Theorem (Peterson)

M is a max-cardinality matching (i.e., it is a matching of maximum cardinality) if and only if there is no M-augmenting path in G.

Remark: If M is a matching and $v_0, \ldots, v_k$ is an M-augmenting path, then

$$M' := M \triangledown \{\{v_i, v_{i+1}\} : 0 \leq i \leq k-1\}$$

is a matching with $|M'| = |M| + 1$.

Hence a max-cardinality matching can be obtaind by repeatedly searching for an M-augmenting path in G ...

Max-cardinality matching on bipartite graphs

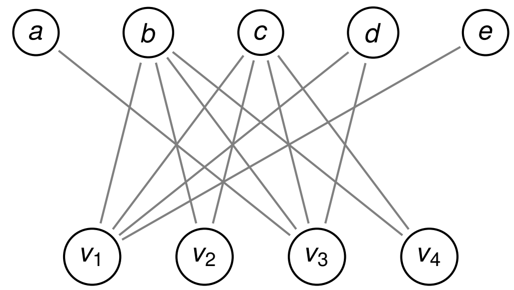
Let $G = \langle U, W, E \rangle$ be a bipartite graph and M be some matching in G.
Define a directed bipartite graph $G_M = \langle U, W, A \rangle$ by

$$\begin{aligned} A := & \{(w,u) : \{u,w\} \in M, u \in U, w \in W\} \cup \\ & \{(u,w) : \{u,w\} \in E \setminus M, u \in U, w \in W\} \end{aligned}$$

Each directed path in G_M is M-alternating.
If such a path starts and ends in an M-free vertex (starts in U, ends in W), it is an M-augmenting path in G.
If no M-augmenting path can be found, M is a max-cardinality matching.

This can be used to compute a max-cardinality matching in time $\mathcal{O}(|U| \cdot |A|)$ (van der Waerden and König)
...can be improved to $\mathcal{O}(\sqrt{|U|} \cdot |A|)$ (Hopcroft and Karp)

Example: Computing a max-cardinality matching



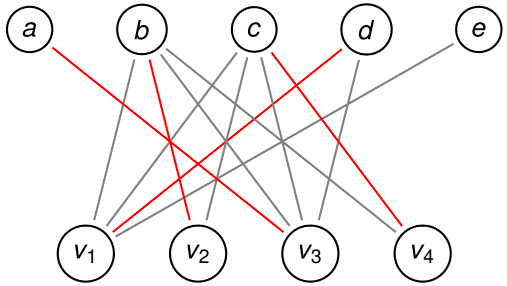
...and max-cardinality matching
$M = \{\{v_4, b\}, \{v_2, c\}, \{v_1, e\}, \{v_3, a\}\}$

All-different constraint and matching

Let $V = \{v_1, \ldots, v_n\}$ be a set of variables and G be the value graph of V. Let $(d_1, \ldots, d_n)$ be a variable assignment.

Lemma

$(d_1, \ldots, d_n) \in \mathit{alldifferent}(v_1, \ldots, v_n)$ if and only if $M = \{\{v_1, d_1\}, \ldots, \{v_n, d_n\}\}$ is a matching in G.



Arc-consistent all-different constraint

Lemma

The constraint $\mathit{alldifferent}(v_1, \ldots, v_n)$ is generalized arc-consistent if and only if every edge in G belongs to a matching in G that covers V.

Proof.

Simple (exercise!). □

Edges in max-cardinality matchings

Theorem

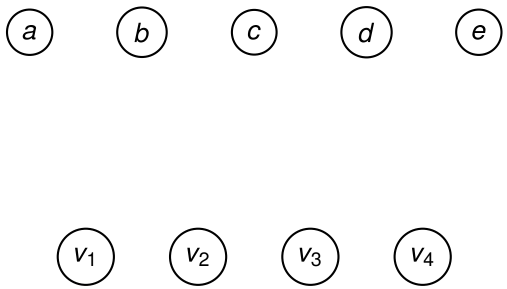
Let G be a graph and let M be a max-cardinality matching in G. An edge e belongs to some max-cardinality matching in G if and only if one of the following conditions holds:

- *$e \in M$.*
- *e is on an even-length M-alternating path starting at an M-free vertex;*
- *e is on an even-length M-alternating cycle.*

Enforcing arc consistency on all-different constraints

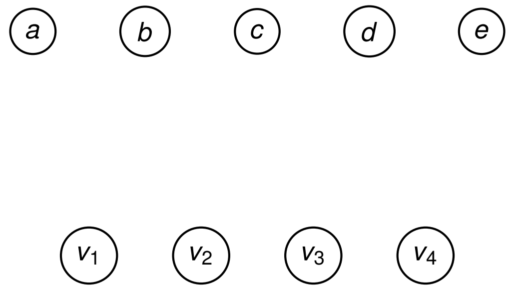
1. Compute a max-cardinality matching M in the value graph of V (can be done in time $\mathcal{O}(m\sqrt{n})$ where $m = \sum_{1 \le i \le n} |D_i|$)
2. Identify the even M-alternating paths starting in an M-free vertex and the M-alternating cycles:
   1. Define dir. bipartite graph $G_M^* = \langle V, D_V, A \rangle$ with $A = \{(v,d) : v \in V, \{v,d\} \in M\} \cup \{(d,v) : v \in V, \{v,d\} \in E \setminus M\}$
   2. Compute the strongly connected components in G_M (in time $\mathcal{O}(n+m)$)
   3. Mark arcs between vertices in the same component as “used”: they belong to an even M-alternating cycle
   4. Marc arcs as “used” that belong to a M-alternating path in G_M that starts in an M-free vertex (breadth-first search in time $\mathcal{O}(m)$).
3. Update $D_v \leftarrow D_v \setminus \{d\}$ for all edges $\{v,d\}$ where the corresponding arc is not marked as “used”.

Example: Enforcing arc-consistency



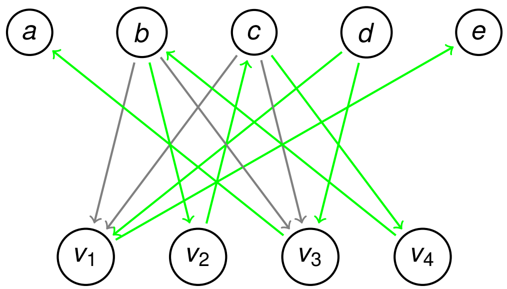
Start from max-cardinality matching

Example: Enforcing arc-consistency



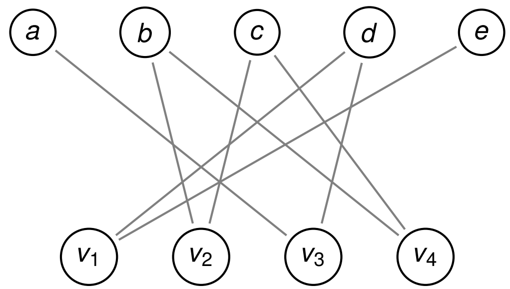
Compute strongly connected components
(e.g. by Kosaraju's algorithm)

Example: Enforcing arc-consistency



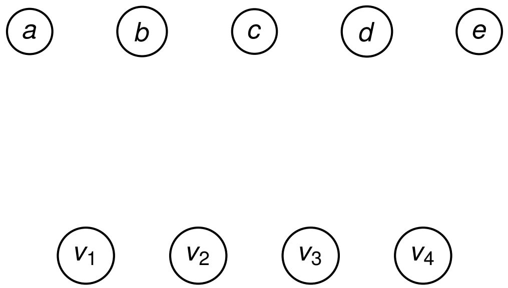
Mark "used" arcs

Example: Enforcing arc-consistency



. . . and remove unused arcs

Example: Enforcing arc-consistency



The `all-different` constraint is now arc-consistent

Literature

Willem-Jan van Hoeve and Irit Katriel.
Global Constraints,
Handbook of Constraint Programming, Elsevier, 2006